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Abstract: On-line sensor monitoring systems aim at detecting anomalies in sensors and reconstructing their correct signals during operation. Auto-associative regression models are usually adopted to perform the signal reconstruction task. In full scale implementations however, the number of sensors to be monitored is very large and cannot be handled effectively by a single reconstruction model. This paper tackles this issue by resorting to an ensemble of reconstruction models in which each model handles a small group of signals. In this view, firstly a procedure for generating the signal groups must be set. Then, a corresponding number of signal reconstruction models must be built on the bases of the groups and, finally, the outcomes of the reconstruction models must be aggregated. In this paper, three different signal grouping approaches are devised for comparison: pure-random, random-filter and random-wrapper. Signals are then reconstructed by Evolving Clustering Method (ECM) models. The median of the outcomes distribution is here retained as the ensemble aggregate. The ensemble approach is applied to a real case study concerning the validation and reconstruction of 792 signals measured at the Swedish boiling water reactor located in Oskarshamn.

Keywords: Sensor monitoring, Signal reconstruction, Ensemble, Evolving Clustering Methods.

1. INTRODUCTION

Plant monitoring relies on the signals collected by a large number of sensors placed at various locations in the plant. Sensors contribute to the safe and efficient operation of modern plants by conveying information on the plant state to the automated controls and the operators. In this view, the measured signals are transmitted to these systems to evaluate the plant health state and eventually take corrective or emergency actions for safely steering critical situations and preventing accidents. To avoid misleading information which may lead to unsafe and/or inefficient actions, it is important to detect sensor malfunctions and possibly reconstruct the incorrect signals. This requires monitoring the sensor performance and being able to promptly detect eventual sensor failures. This leads to increasing confidence in the recorded values of the monitored parameters, with important consequences on system operation, production and accident management and bears also the potential benefit of reducing unnecessary sensor maintenance [1, 2].

In many practical applications, auto-associative models have been used for signal validation [3, 4]. Nevertheless, a limitation of such models is that they can only handle a limited number of signals, whereas in practice thousands of signals must be validated.

The problem is here tackled by resorting to an ensemble-based signal reconstruction procedure. Ensembles of models are indeed an effective approach to tackle complex, large-scaled problems for they allow substituting the use of a single, optimal model (hard to develop as the problem becomes complex) with the use of multiple, non-optimal models, provided their outcomes are properly aggregated. Furthermore, adopting ensembles of diverse models enhances the robustness of the ensemble-aggregated output [5-8].

The ensemble approach hereby developed is founded on the subdivision of the set of sensor signals into small, diverse, yet overlapping groups, the development of a reconstruction model for each group of signals and the aggregation of the outcomes of the individual models to obtain the reconstructed signal values.

The generation of the groups of signals is the main focus of this work. In this respect, the selection of the signals to insert in each group should be driven by both the individual properties of the groups (such as the mutual information content of the signals in the groups and the group size) and the global properties related to the ensemble of models (such as the signal diversity between the groups, the signal redundancy and the ensemble size) [5, 9-15].

To enhance the global ensemble properties, groups have been randomly generated resorting to the Random Feature Selection Ensemble (RFSE) technique [12, 16]. Nevertheless, this *pure-random* technique completely discards the individual properties of the groups. For this reason, two more refined, yet random-based grouping approaches have been developed. These approaches have been devised in order to account also for the individual properties of the groups and are hereby called *random-filter* and *random-wrapper*.

Both techniques are based on the random sampling of a signal. In the *random-filter* approach, the group in which inserting the randomly sampled signal is empirically selected as the one that provides the highest correlation between the sampled signal and the others already included in the group. On the contrary, the *random-wrapper* approach directly accounts for the performance of the model effectively used for reconstructing the signals, and thus the randomly sampled signal is inserted in the group whose corresponding model provides the best signal reconstruction performance.

Evolving Clustering Method (ECM)-based models [17] have been adopted to reconstruct the signals. ECM models are robust and demand a short training process, making them suitable for the multiple-model ensemble approach.

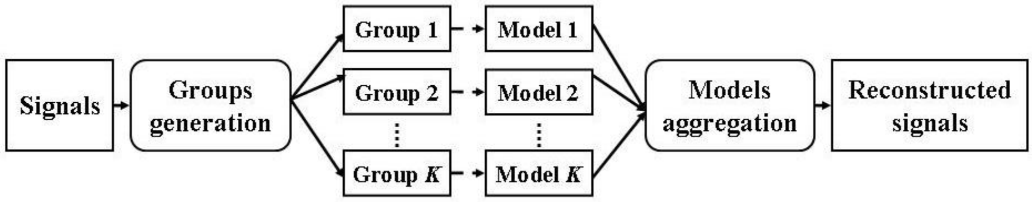
The median of the outcomes distribution is retained as the ensemble output. This allows avoiding the inclusion in the ensemble aggregate of largely incorrect models' signal reconstructions (conjectured to lie on the tails of the outcomes distribution) possibly due to the complete or partial group randomization [13-15].

Section 2 illustrates in details the multi-group ensemble approach hereby developed. In Section 3 the method is applied to a real case study concerning the reconstruction of 792 signals measured at a Swedish nuclear boiling water reactor. Conclusions are drawn in the last Section.

2. THE MULTI-GROUP ENSEMBLE APPROACH

Figure 1 illustrates the multi-group ensemble approach. As previously stressed, the approach proceeds in three steps: (1) the generation of the groups of signals, (2) the development of the models for reconstructing the signals and (3) the aggregation of the outcomes of the individual models based on the groups.

Figure 1: The multi-group ensemble approach to signal reconstruction



Concerning the first problem, the selection of the signals to insert in each group should be driven by both the individual properties of the groups and the global properties related to the ensemble of models. Concerning the group individual properties, signals should be inserted in a group in such a way that:

- the mutual information content of the signals in the group is high for it leads to better reconstruction performances of the associated individual model [5, 10, 11];
- the groups size is small since models based on a reasonably small number of signals are easier to develop [5, 9-11].

Coming to the global ensemble properties, the groups must:
- be diverse in terms of signal composition for that leads to having diverse models and thus an increased ensemble robustness [5-8];
- ensure a good signal redundancy, i.e. an adequate number of diverse groups containing a same signal [5, 9];
- be limited in number since that helps reducing the computational cost.

Operatively, the average size of the groups $\langle m \rangle$ in the ensemble and the redundancy of the signals R in the groups have been decided a priori based on empirical considerations related to the case study under analysis. Given these two parameters and the total number of signals n to validate and reconstruct, one can immediately calculate the number of groups to generate using the identity [12][1]:

$$\langle m \rangle K = nR \tag{1}$$

To ensure adequate diversity and signal redundancy, groups must partially overlap (in order to have each signal included in more than one group), while still being sufficiently diverse among one another.

To this aim, groups are randomly generated resorting to the Random Feature Selection Ensemble (RFSE) technique [12, 16]. The RFSE technique consists in randomly sampling a signal $i = 1, 2, ..., n$ and inserting it in a randomly sampled group $k = 1, 2, ..., K$, provided that the sampled signal has redundancy R_i smaller than R and that the sampled group has size m_k smaller than m_{MAX}. Randomizing the features of the groups (upon which the signal reconstruction models are built) with the RFSE technique allows obtaining highly diverse signal groups and, correspondingly, diverse signal outcomes from the individual models within a fast group generation process.

Nevertheless, this pure-random technique seeks no optimization of the composition of the individual groups, i.e. no relevance is given, for example, to the correlation between the signals in the groups or to their capability of efficiently reconstructing one another.

The random-filter and random-wrapper approaches here presented tackle this problem. Both techniques are based on the random sampling of a signal $i = 1, 2, ..., n$. In filter approaches, the algorithm for evaluating the goodness of the groups functions as a filter, i.e. the decision of including or discarding the sampled signal in a group is based on characteristics judged to be (indirectly) favorable for signal validation and reconstruction, independently of the specific model which is then used to reconstruct the signals. The correlation between the signals in the group is typically used as an indirect measure for comparing the goodness of the groups. In this view, in the random-filter approach, the group in which inserting the randomly sampled signal is empirically selected as the one that provides the highest correlation between the sampled signal and the others already included in the group. This criterion is intuitively motivated by the fact that the signals in the groups are used to build models for their reconstruction and by the conjecture that strongly positively or negatively correlated signals are capable of regressing one another. In fact, the information content of strongly negatively correlated signals is also very high and comparable to the one derived from strongly positively

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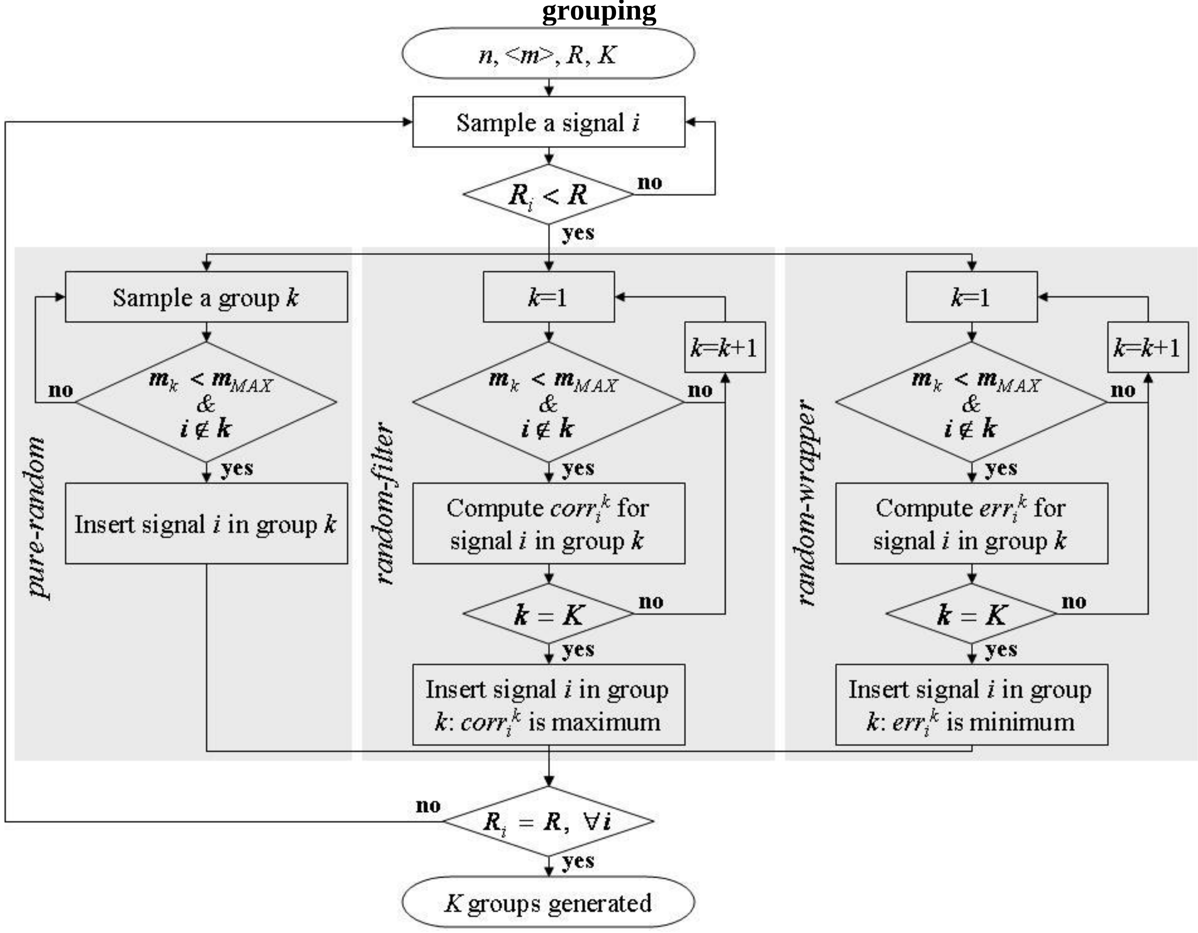
[1] Notice that by setting the average group size $\langle m \rangle$ and a maximum allowed group size m_{MAX} groups are going to range from an unknown minimum number of signals to m_{MAX} having on average $\langle m \rangle$ signals, each one appearing in R different groups, i.e. with the same redundancy.

correlated signals. The measure herein used to quantify these characteristics is the Pearson's correlation coefficient [5, 10, 11].

On the contrary, in wrapper approaches the algorithm to evaluate the goodness of the groups behaves as a "wrapper" around the specific model used for the validation and reconstruction of the signals; during the grouping process, the performance of the validation and reconstruction model itself is directly used as evaluation function to compare the different candidate groups [11, 18]. Therefore, in the random-wrapper approach the randomly sampled signal is inserted in the group whose corresponding model provides the best reconstruction performance for that signal, i.e. the smallest reconstruction error computed on a set of test samples[2].

This way of proceeding allow controlling of the ensemble parameters (group size, signal redundancy and ensemble size) and maintaining high diversity between the groups in the ensemble while accounting also for the mutual information between the signals inserted in the groups. The three grouping approaches hereby developed are sketched in Figure 2.

Figure 2: Sketch of the pure-random, random-filter and random-wrapper approaches to signal grouping



With respect to the type of model to adopt for reconstructing the signals, a number of aspects must be taken into account. Indeed, models must be accurate and provide a correct reconstruction of the signals. Nonetheless, the models' robustness is a fundamental aspect to take into consideration: in fact,

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[2] The reconstruction error for signal i by group k is simply obtained by averaging over the N_{tst} test samples the differences between the real signal values $f_i(t)$, $t=1,2,...,N_{tst}$ and the corresponding predictions of group k, $\hat{f}_i^k(t)$, $t=1,2,...,N_{tst}$ .In the application that follows, signals are previously normalized in the range [0.2, 1], for convenience.

in case sensors failures lead to producing corrupted measurements of the physical quantity of interest and thus conveying wrong information to the plant monitoring systems, the model must be capable of reconstructing the correct signal values by exploiting the information carried by the other signals. Finally, since the multi-group ensemble approach provides for the development of a considerable number of models, the adoption of simpler, yet fast models is preferable to using complex models which require time-consuming training processes. This is especially valid if signal grouping is based on the random-wrapper approach which provides for the development of an extremely large number of models during the group generation phase.

The ECM model here adopted fulfills these requirements. In fact, the ECM is a fast, one-pass algorithm for dynamic clustering of an input stream of data. It is a distance-based clustering method where the cluster centres are represented by evolved nodes in an on-line mode. The clustering process starts with an empty set of clusters. The data stream, i.e. the training samples, is used to generate a number of multi-dimensional clusters identified by their position in the sample space and thier width. Given a maximum allowed cluster width, during the training process, the position and width of the clusters are continuously updated and a near-optimal cluster distribution is eventually obtained. Based on these clusters, the model is expected to generalize by associating to an unseen sample the (multi-dimensional) value of the centre of the closest cluster [17].

Regarding the aggregation of the outcomes of the individual models, when adopting the pure, filter or wrapper methods for signal grouping, one must account that the (partly) randomized composition of the signal groups is such that some models might provide largely incorrect signal reconstructions which negatively affect the ensemble aggregate. Thus, discarding the outcomes of some models can enhance the accuracy and robustness of the aggregated output.

To reduce the risk of including largely incorrect outcomes in the ensemble aggregate, the median of the outcomes distribution is here considered. This choice is motivated by the randomness of the models outcomes, which, if unbiased, are expected to distribute around the correct (unknown) signal value. In this view, the outcome lying in the centre of the distribution is conjectured to be close to the correct signal value, whereas those lying on the tails of the distribution are considered fairly incorrect [13-15].

The median approach considers for the generic pattern t the single outcome $\hat{f}_i^{k_C}(t)$ lying in the centre of the distribution of the outcomes for that sample, i.e.:

$$\hat{f}_i^{E}(t) = \hat{f}_i^{k_C}(t) \qquad i = 1, 2, ..., n \tag{2}$$

where k_C denotes the index of the model whose outcome is central with respect to the reconstructed values of the K_i models including signal i.

Finally, to evaluate the performance of the ensembles based on the different aggregation techniques, first the absolute ensemble signal reconstruction error is computed using the N_{tst} test samples:

$$\varepsilon_i^E = \frac{1}{N_{tst}} \sum_{t=1}^{N_{tst}} \left| f_i(t) - \hat{f}_i^E(t) \right| \tag{3}$$

Then, the ensemble reconstruction error is retained as the average of the absolute signal reconstruction errors of Eq. (3):

$$\eta^E = \frac{1}{n} \sum_{i=1}^{n} \varepsilon_i^E \tag{4}$$

3. APPLICATION

The proposed grouping approaches are applied for comparison on a data set of n=792 signals measured at a nuclear Boiling Water Reactor (BWR) located in Oskarshamn, Sweden.

A total number N=8476 of 792-dimensional patterns is available. Data signals have been sampled over a 3-year period (2004-2006) from a corresponding number of sensors. Half of the available patterns (randomly sampled) have been used to perform the *random-filter* and *random-wrapper* groupings, i.e. to compute the signals correlations and the signal reconstruction errors of the models. The remaining samples have been randomly divided in a training set (75% of the patterns) to train the ECM models and a test set to compute the ensemble performances (Eq. 3, 4). Based on practical considerations, the required average group size $\langle m \rangle$ has been set equal to 50 allowing a maximum group size $m_{MAX} = 52$. Signal redundancy R has been set equal to 7 for all signals. Once $\langle m \rangle$ and R are set, the number of groups K to generate is obtained from Eq. (1), being therefore equal to 111.

As previously mentioned, the goodness of a signal grouping approach can be measured in terms of the diverse signal composition of the groups. An empirical measure is here proposed to verify the diversity between the groups in the ensemble. Let us consider a generic ensemble of K groups with different sizes m_k, $k = 1,2,...,K$. The pair-wise diversity between two generic groups k_1 and k_2 of sizes m_{k_1} and m_{k_2}, respectively, can be computed as:

$$div^{k_1,k_2} = \frac{1}{1+\exp(12\beta_{com}^{k_1,k_2} - 6)} \tag{5}$$

where $\beta_{com}^{k_1,k_2} = n_{com}^{k_1,k_2} \big/ \max\left\{m_{k_1}, m_{k_2}\right\}$ is the normalized fraction of signals in common between the two groups ($n_{com}^{k_1,k_2}$).

This measure is such that high pair-wise diversity values are assigned to those pairs of groups whose fraction of common signals is relatively low (i.e. if $\beta_{com}^{k_1,k_2} \to 0$, $div^{k_1,k_2} \to 1$), whereas it penalizes group pairs with too many signals in common (i.e. if $\beta_{com}^{k_1,k_2} > 0.5$, $div^{k_1,k_2} < 0.5$).

To compute the diversity at the level of the ensemble of groups, first the diversity for each signal $i = 1,2,...,n$ is calculated. Considering the generic signal i included in K_i groups, the signal diversity d^i is taken as the average of its K_i groups' pair-wise diversities div^{k_1,k_2}, $k_1, k_2 = 1,2,...,K_i$, $k_1 \neq k_2$, viz.:

$$d^i = \frac{1}{K_i}\sum_{k_1=1}^{K_i}\left(\frac{1}{K_i - 1}\sum_{\substack{k_2=1 \\ k_2 \neq k_1}}^{K_i} div^{k_1,k_2}\right) \tag{6}$$

The ensemble diversity δ is, then, simply computed as the average of the signals diversities:

$$\delta = \frac{1}{n}\sum_{i=1}^{n} d^i \tag{7}$$

Table 1 compares the *pure-random*, *random-filter* and *random-wrapper* approaches in terms of the required computational time, ensemble diversity (Eq. 7) and the ensemble reconstruction error (Eq. 4).

The *pure-random*, based on random sampling of both signals and groups, ensures the highest signal diversity in the groups with the smallest computational effort. On the other hand, the *filter* and *wrapper* approaches generally obtain smaller ensemble diversities and require larger computational times (especially the *random-wrapper*). In this respect, notice that signal grouping is performed off-line and therefore the related computational cost will not affect the effectiveness of the on-line signal reconstruction.

The diversity-reduction effect is especially marked in the *random-filter* approach and can be explained by the presence of subsets of highly correlated signals which tend to generate similar groups; instead, the *random-wrapper* approach maintains high signal diversities thanks to the fact that highly correlated signals do not necessarily ensure the best model performances and therefore similar subsets of signals are not likely to be inserted in many groups.

The *random-filter* approach combined with the median achieves no improvement with respect to the *pure-random* approach. In fact, the loss of signal diversity between the groups most likely leads to having very similar (i.e. biased) model predictions for a signal, which therefore are not distributed around the correct signal value, as previously conjectured. This also reveals that in the *random-filter* approach the advantage of an increased signal mutual information in the groups and the disadvantage of a decreased group diversity have compensated each other; on the contrary, in the *random-wrapper* approach the higher signal reconstruction capability of the individual models coupled with a high diversity between the groups allows achieving the best ensemble reconstruction performances.

Table 1: Computational cost, ensemble diversities and reconstruction errors obtained by the *pure-random*, *random-filter* and *random-wrapper* approaches

	pure-random	***random-filter***	***random-wrapper***
Computational time	< 1 minute	Approx. 5 minutes	Approx. 100 minutes
δ	0.9939	0.8259	0.9687
η^{E}	0.00603	0.00605	0.00530

Nevertheless, a robust ensemble of models must be capable of reconstructing the signals when in presence of sensor failures, such as drifts. Within the proposed ensemble approach, a faulty sensor sends a faulty signal in input to the reconstruction models which include that signal; in this situation, the ensemble of models should still be capable of providing a good estimate of the true value of the signal by exploiting the information coming from the non-faulty signals in the groups of the ensemble.

The robustness of the three grouping approaches has been specifically tested for comparison on the reconstruction of faulty signals in case of multiple sensor failures. Ten signals have been chosen as objects of the analysis. Approximately, the first third of the signal test samples has been left undisturbed as in the normal operation, while, in order to simulate a sensor failure, a linear drift has been introduced in the remaining test values.

Figure 3 shows the ensemble signal reconstruction errors (Eq. 3) for the ten drifted signals obtained with the *pure-random*, *random-filter* and *random-wrapper* grouping approaches, respectively. The random-wrapper approach provides the best performances for all signals and ensures the smallest spill-over effect[3] ($S^{tot}_{pure-random} = 0.1656$ vs. $S^{tot}_{random-filter} = 0.1734$ vs. $S^{tot}_{random-wrapper} = 0.1546$).

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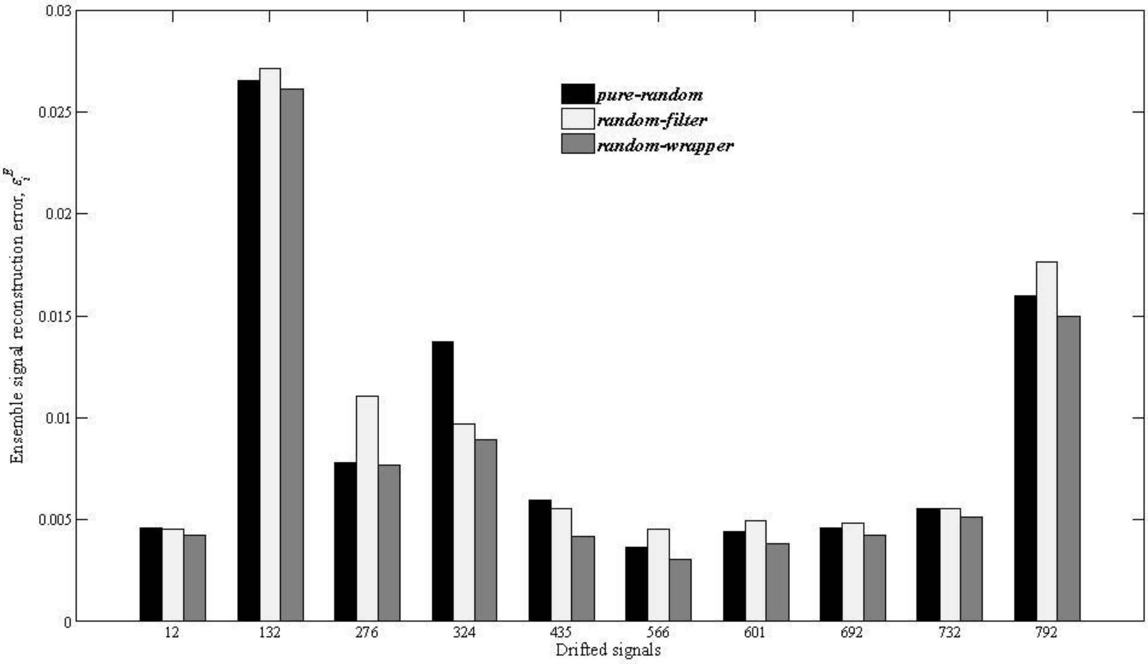
[3] Spill-over is the detrimental effect on the reconstruction of undisturbed signals when some signals are disturbed. It is computed in terms of signal sensitivity as done in [19]. For each signal not affected by disturbs we compute the average deterioration in its reconstruction when other signals are affected by disturbs. Given two generic signals i_1 and i_2, the sensitivity of i_1 undisturbed with respect to i_2

Finally, Figure 4 shows the reconstruction of drifted signal 792 obtained by the *random-wrapper* ensemble. The reconstruction (top graph in the Figure) is very close (sometimes superposed) to the real signal value and does not see the drift. This can be also seen by the residual (bottom graph in the Figure) which is computed as the difference between the measured and reconstructed signal values. Notice that residuals are the parameters upon which sensor monitoring systems usually perform the sensors diagnosis: when residuals exceed some thresholds, the system reports the presence of a sensor failure. For this reason, early sensor fault detection requires right and prompt information from the residuals which is here effectively conveyed by the developed ensemble signal reconstruction procedure.

Figure 3: Ensemble signal reconstruction errors for ten drifted signals obtained with *the pure-random, random-filter* and *random-wrapper* grouping approaches, respectively



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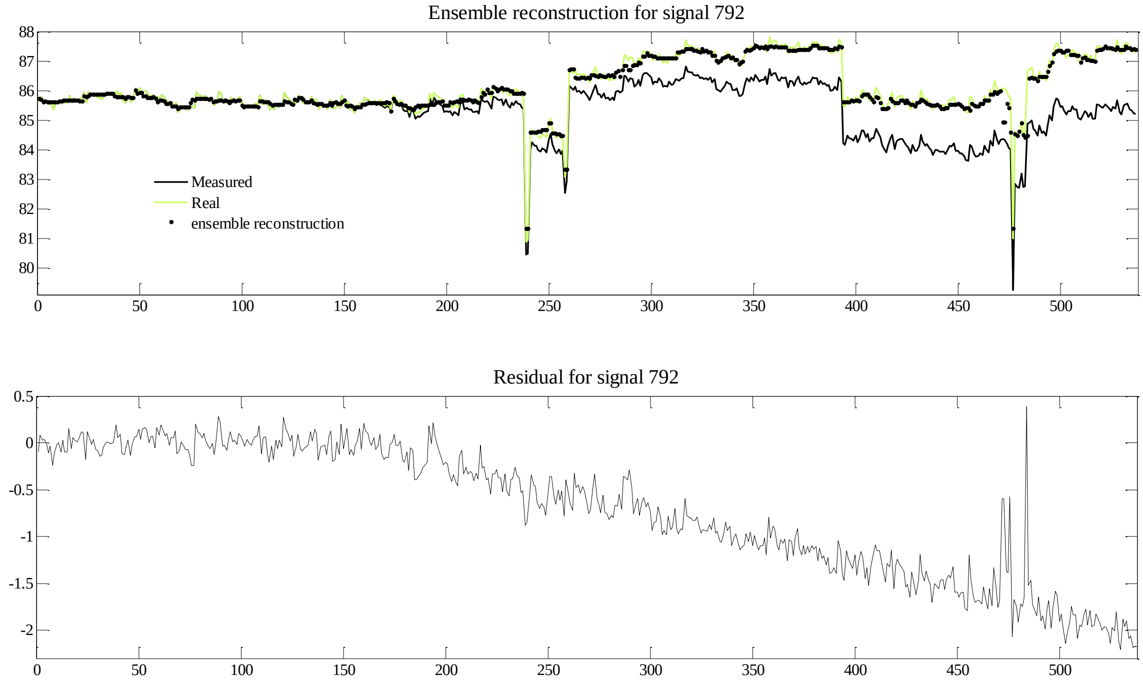
disturbed is defined as $S_{i_1} = \dfrac{\left| \hat{f}_{i_1|i_2 \in D} - \hat{f}_{i_1|i_2 \notin D} \right|}{\left| f_{i_2|i_2 \in D} - f_{i_2|i_2 \notin D} \right|}$, where D is the set of disturbed signals, $\hat{f}_{i_1|i_2 \in D}$ and $\hat{f}_{i_1|i_2 \notin D}$ are the reconstructions of signal i_1 in case i_2 is disturbed and undisturbed, respectively, while $f_{i_2|i_2 \in D}$ and $f_{i_2|i_2 \notin D}$ are the measured values of i_2 when the signal is disturbed and undisturbed, respectively. By computing the sensitivity for i_1 considering one by one all the disturbed signals $i_2 = 1, 2, ..., n_D$, one obtains the average signal sensitivity $\langle S_{i_1} \rangle$ for undisturbed signal i_1 which tends to 1 if i_1 is strongly affected by disturbs on other signals (i.e. the spill-over effect is large) or 0 if the reconstruction of i_1 is not influenced (i.e. the spill-over effect is small). The average spill-over effect is then simply computed as $S^{tot} = \dfrac{1}{n - n_D} \sum_{i \notin D} \langle S_i \rangle$.

Figure 4: Reconstruction of signal 792 (light line) when drifted (dark line) by the *random-wrapper* ensemble (dark dots) and corresponding residuals (bottom graph)



4. CONCLUSIONS

This work has tackled the problem of large-scale signal validation and has shown a practical application regarding signals measured at nuclear power plants.

The strategy hereby followed is based on the use of an ensemble of reconstruction models. In this respect, firstly signals must be grouped into many small, overlapping groups. Then a corresponding number of reconstruction models must be developed and, finally, the outcomes of the models must be opportunely aggregated.

The paper has focussed on methods for generating the groups of signals and three approaches have been proposed: the *pure-random* approach in which signal are randomly sampled and inserted in randomly sampled groups; the *random-filter* and *random-wrapper* approaches according to which the group in which inserting the signal is selected based on the characteristics of the other signals already present in the groups, such as the mutual correlation and the mutual reconstruction capabilities, respectively. Evolving Clustering Method has been used as signal reconstruction model and the median of the model outcomes distribution as ensemble aggregate.

The application has concerned the validation of 792 signals measured at the Oskarshamn boiling water reactor. The random-wrapper approach has demonstrated its superiority in reconstructing correctly the signals, especially when the corresponding sensors are affected by failures which convey corrupted measurements.

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